Cardiovascular Diabetology

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Stress hyperglycemia ratio and machine learning model for prediction of all-cause mortality in patients undergoing cardiac surgery

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Abstract

Background The stress hyperglycemia ratio (SHR) was developed to reduce the effects of long-term chronic glycemic factors on stress hyperglycemia levels, which was associated with adverse clinical outcomes. This study aims to evaluate the relationship between the postoperative SHR index and all-cause mortality in patients undergoing cardiac surgery.

Methods Data for this study were extracted from the Medical Information Mart for Intensive Care IV (MIMIC-IV) database. Patients were categorized into four groups based on postoperative SHR index quartiles. The primary outcome was 30-day all-cause mortality, while the secondary outcomes included in-hospital, 90-day and 360-day all-cause mortality. The SHR index was analyzed using quartiles, and Kaplan–Meier curves were generated to compare outcomes across groups. Cox proportional hazards regression and restricted cubic splines (RCS) were employed to assess the relationship between the SHR index and the outcomes. LASSO regression was used for feature selection. Six machine learning algorithms were used to predict in-hospital all-cause mortality and were further extended to predict 360-day all-cause mortality. The SHapley Additive exPlanations method was used for visualizing model characteristics and individual case predictions.

Results A total of 3,848 participants were included in the study, with a mean age of 68 ± 12 years and female participants comprised 30.6% (1,179). Higher postoperative SHR index levels were associated with an increased risk of in-hospital, 90-day and 360-day all-cause mortality as shown by Kaplan–Meier curves (log-rank $P < 0.05$). Cox regression analysis revealed that the highest postoperative SHR quartile was associated with a significantly higher risk of mortality at these time points ($P < 0.05$). RCS analysis demonstrated nonlinear relationships between the postoperative SHR index and all-cause mortality (P for nonlinear < 0.05). The Naive Bayes model achieves the highest area under the curve (AUC) for predicting both in-hospital mortality (0.7936) and 360-day all-cause mortality (0.7410).

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Conclusion In patients undergoing cardiac surgery, higher postoperative SHR index levels were significantly associated with increased risk of in-hospital, 90-day and 360-day all-cause mortality. The SHR index may serve as a valid tool for assessing the severity after cardiac surgery and guiding treatment decisions.

Keywords Cardiac surgery, Stress hyperglycemia ratio, Prognosis, Machine learning, All-cause mortality

Introduction

Cardiac surgery is a cornerstone in the management of various cardiovascular conditions and plays a pivotal role in improving patient outcomes. It is routinely performed to address pathologies such as coronary artery disease, valvular heart disease, congenital heart defects, and aortic aneurysms. Among these, coronary artery bypass grafting (CABG) and valve repair surgeries are the most commonly performed procedures [1, 2]. These complex surgeries often require thoracotomy to provide direct access to the heart and typically involve cardiopulmonary bypass to temporarily arrest cardiac function while maintaining systemic circulation [3].

Despite significant advancements in surgical techniques, anesthetic management, and perioperative care, cardiac surgery remains a high-risk procedure, particularly for elderly individuals and those with multiple comorbidities. Postoperative complications—including infection, hemorrhage, organ dysfunction, and mortality—continue to pose substantial challenges [4, 5, 6]. National data indicate that the inpatient mortality rate for cardiac surgery is approximately 2.1%, underscoring the need to address postoperative risks effectively [7]. Identifying determinants of mortality and developing personalized risk assessment and management strategies are essential for improving patient outcomes.

Blood glucose management is a crucial aspect of caring for critically ill patients, particularly those undergoing cardiac surgery. Hyperglycemia is closely linked with an increased incidence of myocardial infarction, heart failure, cerebrovascular events, and elevated mortality rates [8, 9, 10]. However, a single measurement of blood glucose at admission does not provide a comprehensive picture of a patient's long-term glycemic control. Glycated hemoglobin (HbA1c), which reflects average blood glucose levels over the past 8 to 12 weeks, offers a more accurate assessment of glycemic status. The stress hyperglycemia ratio (SHR), a composite index derived from both admission blood glucose and HbA1c, has been proposed as a more reliable marker of the glycemic response to acute stress [11]. Stress-induced hyperglycemia, mediated by elevated levels of glucagon, cortisol, catecholamines, and growth hormone, results in enhanced gluconeogenesis, accelerated glycogenolysis, and reduced peripheral glucose uptake [12, 13]. Recent studies indicate that a higher SHR is associated with adverse cardiovascular outcomes, including an increased risk of heart failure and myocardial infarction [14, 15].

Given the limited research on the relationship between postoperative SHR and postoperative mortality in cardiac surgery, this study aims to investigate the association between postoperative SHR and all-cause mortality following cardiac surgery. Through this investigation, we hope to identify high-risk patients at an early stage and inform the development of targeted strategies to optimize postoperative care and improve long-term survival.

Method

Source of data

This study is a retrospective analysis utilizing data from the publicly available Medical Information Mart for Intensive Care IV (MIMIC-IV, version 3.1) database. MIMIC-IV, an enhancement of its predecessor MIMIC-III, includes updated data and reconstructed tables. It contains clinical information from over 190,000 patients and 450,000 hospitalizations recorded between 2008 and 2019 at the Beth Israel Deaconess Medical Center in Boston, MA, United States. The database provides comprehensive records on patient demographics, laboratory tests, medications, vital signs, surgical procedures, disease diagnoses, medication management, and follow-up survival status. To access the data, we completed the National Institutes of Health training course on protecting human study participants and passed the Collaborative Institutional Training Initiative exams. The database does not contain protected health information, and all patient data is anonymized.

Study design and population

Our analysis included patients who were aged 18–100 years old and undergone a cardiac surgery including CABG, valve surgery and combining CABG and valve surgery (eTable 3). Patients were excluded based on the following criteria: (1) those lacking HbA1c (2) those lacking fasting blood glucose data within 24 h after cardiac surgery; (3) those without prognostic information. Ultimately, 3,848 patients met the inclusion criteria and were categorized into four groups based on quartiles of the postoperative SHR index (Fig. 1).

Data extraction

Data extraction was performed using Navicat Premium (Version 16.1.15) with SQL. The study examined various variables categorized as follows: Demographics: age, sex. Past medical history: conditions such as myocardial infarction (MI), heart failure (HF), cerebrovascular

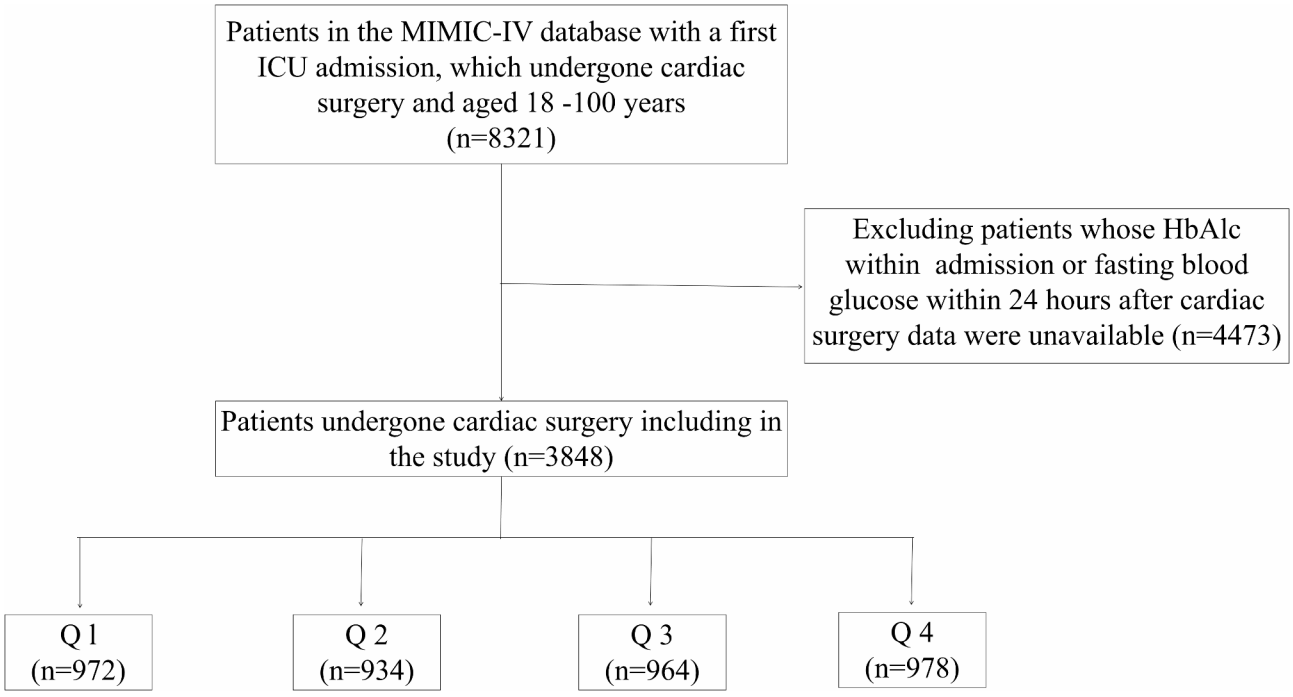

Fig. 1 Flow of included patients through the trial. *SHR* Stress hyperglycemia ratio; *HbA1c* Hemoglobin A1c

disease (CVD), pulmonary disease, diabetes, renal disease. Laboratory indicators: preoperative and postoperative fasting blood, white blood cells (WBC), neutrophils, monocytes, lymphocytes, platelets and creatinine; HbA1c of admission. Vital signs: heart rate (HR), systolic blood pressure (SBP), diastolic blood pressure (DBP), respiratory rate (RR), and temperature (T). Length of stay (LOS) and outcomes: duration of mechanical ventilation, LOS in hospital, LOS in ICU, hospital, 30-day, 90-day, and 360-day all-cause mortality. Disease Severity Scores: Acute Physiology Score III (Aps iii).

Outcomes

The primary outcome of this study was 30-day all-cause mortality, while the secondary outcomes included in-hospital, 90-day and 360-day all-cause mortality.

Calculation of SHR, NLR, MLR, PLR, SII, and SIRI

SHR = [(glucose max (mg/dl))/(28.7×HbA1c (%)-46.7)]; [15] NLR = neutrophil count/lymphocyte count; [16] MLR = monocyte count/lymphocyte count; [17] PLR = platelet count/lymphocyte count; [18] SII = platelet count×neutrophil count/lymphocyte count; [19] SIRI = neutrophil count×monocyte count/lymphocyte count [20].

Statistical analysis model development

A normality test was conducted on continuous variables. For non-normally distributed data, the Wilcoxon rank-sum test was applied, and results were expressed as medians with interquartile ranges (IQR). Categorical variables were analyzed using Chi-square or Fisher's exact tests and presented as absolute numbers with percentages. Kaplan–Meier (KM) curves were used to determine the incidence of primary and secondary outcomes, stratified by the SHR index. Multivariable Cox proportional hazards regression models assessed the relationship between the SHR index and all-cause mortality. The lowest quartile of the SHR index served as the reference group. The SHR index was also analyzed as a continuous variable to predict all-cause mortality using area under the curve (AUC). In addition, The SHR index using restricted cubic splines (RCS) to explore the dose-response relationship with the risk of primary and secondary outcomes. Stratified analyses were performed based on gender (male, female), age (≤75 years or >75 years), creatinine (≤90 mg/dl or >90 mg/dl), MI, HF, CVD, pulmonary disease, diabetes, and renal disease status. Causal mediation analysis was used to explore the mediating role between postoperative SHR and 30-day all-cause mortality.

Due to the presence of class imbalance in the dependent variables, undersampling was utilized to adjust the dataset and achieve class balance. Subsequently, the dataset was partitioned into a training set and an internal validation set using the Synthetic Minority Over-Sampling Technique. For datasets with a high number of features, Lasso regression was applied for feature selection. This technique incorporates L1 regularization, which not only facilitates feature selection but also reduces

dimensionality by compressing the coefficients, effectively retaining features with significant contributions while eliminating redundant ones.

In the present study, six machine learning algorithms—namely, extreme gradient boosting (XGBoost), support vector machine (SVM), adaptive boosting (AdaBoost), naive Bayes (NB), logistic regression (LR), and gradient boosting machine (GBM)—were used to predict in-hospital all-cause mortality and were further extended to predict 360-day all-cause mortality. The features selected through Lasso regression were incorporated into the model. To ensure the robustness of the model, ten-fold cross-validation was performed. Grid search optimization was utilized to identify the most suitable hyperparameters for each algorithm. During the parameter tuning process, the model with the highest area under the receiver operating characteristic curve was selected as the optimal model. The final models were trained using the training set, and their performance was evaluated on both the internal and external validation sets. The effectiveness of the predictive model was assessed using the AUC of the ROC curve.

All statistical analyses were conducted using SPSS software (version 22.0, IBM Corporation, United States) and R software (version 4.3.1, R Foundation for Statistical Computing, Austria), with a significance level set at $P < 0.05$. YP completed all of statistical analysis.

Results

Baseline characteristics of study participants

This study analyzed data from 8,321 patients included in the MIMIC-IV database, of whom 3,848 met the inclusion criteria. Participants were stratified into four quartiles (Q1, Q2, Q3, and Q4) according to postoperative SHR percentiles. The baseline characteristics for each group are detailed in Table 1. The mean age of the cohort was 68 ± 12 years, with female participants comprising 30.6% (1,179). It is noteworthy that the Q4 group demonstrated the highest mean age and the largest proportion of female participants. The most prevalent comorbidities included MI, and HF, affecting 40.0%, and 37.6% of the population, respectively, with the Q4 group having the highest prevalence of these conditions. Furthermore, preoperative and postoperative WBC counts, creatinine levels, aps iii, and durations of mechanical ventilation, ICU stays, and total hospitalizations were consistently highest in the Q4 group.

Relationship between postoperative SHR and clinical outcomes

Clinical outcomes varied significantly across postoperative SHR quartiles. Patients in the Q4 group exhibited the highest rates of in-hospital mortality (4.9%), 30-day mortality (4.7%), 90-day mortality (7.9%), and 360-day mortality (12.5%). An adjusted logistics regression analysis, accounting for sex, age, MI, HF, CVD, pulmonary disease, diabetes, renal disease, duration of mechanical ventilation, aps iii, and preoperative creatinine and WBC levels, revealed Q4 patients exhibiting higher risks of in-hospital mortality (OR = 3.323; 95% CI 1.558–7.089; $p = 0.002$), 30-day mortality (OR = 2.877; 95% CI 1.391–5.590; $p = 0.004$), 90-day mortality (OR = 1.918; 95% CI 1.187–3.099; $p = 0.008$), and 360-day mortality (OR = 1.485; 95% CI 1.031–2.138; $p = 0.034$). By contrast, no significant differences were observed between Q2 and Q1, or Q3 and Q1 (Table 2). These findings indicate that patients with an SHR index of ≥ 1.40 have a higher risk of in-hospital, 30-day, 90-day and 365-day all-cause mortality compared to those with an SHR index of < 1.40. Similar trends were observed for in-hospital, 30-day, 90-day and 365-day all-cause mortality, as detailed in Fig. 3.

Survival analysis

Kaplan–Meier survival analyses revealed significant differences in survival rates across postoperative SHR quartiles for in-hospital, 90-day and 360-day all-cause mortality. Patients in the Q4 group experienced lowest survival rates at all time points compared to those in lower postoperative SHR quartiles (log-rank $p < 0.05$). However, survival rates did not differ significantly among the Q1, Q2, and Q3 groups across any time point (Fig. 2).

Predictive value and nonlinear relationship

The prognostic utility of preoperative SHR, postoperative SHR, and the rate of SHR change for in-hospital, 30-day, 90-day, and 360-day mortality was assessed using AUC analysis. Among these, postoperative SHR exhibited the strongest predictive value, with AUCs of 0.723, 0.710, 0.658, and 0.618, respectively (eFigure 1). Moreover, restricted cubic spline (RCS) analysis indicated a nonlinear association between postoperative SHR and all-cause mortality at all time points (in-hospital, 30-day, 90-day, and 360-day all-cause mortality). Increasing postoperative SHR values were consistently associated with higher mortality risks, demonstrating the nonlinear nature of this relationship (p for nonlinear < 0.05) (Fig. 3).

Stratified analyses

Subgroup analyses were conducted to explore potential effect modifications by sex, age, MI, HF, CVD, pulmonary disease, diabetes, and renal disease on the association between postoperative SHR and in-hospital, 30-day, 90-day, 360-day all-cause mortality (eFigure 2–5). Postoperative SHR was significantly associated with 30-day mortality among males, individuals aged ≤ 75 years, those with creatinine levels > 90, patients with MI, those without heart failure, individuals with CVD, and those without pulmonary or renal disease ($p < 0.05$). Conversely,

Table 1 Baseline characteristics of patients grouped according to postoperative SHR index quartiles

Variables	Total, *N* = 3848	Q1 (SHR ≤ 1.06), *N* = 972	Q2 (1.06< SHR ≤ 1.20), *N* = 934	Q3 (1.20< SHR ≤ 1.40), *N* = 964	Q4 (SHR ≥ 1.40), *N* = 978	*P* value
Age, y	68 ± 12	67 ± 12	68 ± 11	68 ± 11	69 ± 11	0.001*
Female, (%)	1179 (30.6)	318 (32.7)	277 (29.7)	259 (26.9)	325 (33.2)	0.008*
BMI Mean, kg/m2	29.1 ± 6.0	29.5 ± 6.4	28.9 ± 5.6	29.2 ± 6.0	28.7 ± 6.0	0.026*
Past medical history						
Myocardial infarct, (%)	1538 (40.0%)	379 (39.0)	349 (37.4)	385 (39.9)	425 (43.5)	0.046*
Heart failure, (%)	1446 (37.6)	312 (32.1)	302 (32.3)	342 (35.5)	490 (50.1)	0.000*
Cerebrovascular disease, (%)	436 (12.0)	115 (11.8)	111 (11.9)	109 (11.3)	128 (13.1)	0.667
Chronic pulmonary disease, (%)	910 (23.6)	228 (23.5)	235 (25.2)	203 (21.1)	244 (24.9)	0.127
Diabetes, (%)	1474 (38.3)	454 (46.7)	278 (29.8)	325 (33.7)	417 (42.6)	0.000*
Renal disease, (%)	801 (20.8)	161 (16.6)	172 (18.4)	188 (19.5)	280 (28.6)	0.000*
Preoperative laboratory indicators						
Glucose max, mg/dl	134.8 ± 57.1	134.2 ± 59.8	123.9 ± 42.6	130.3 ± 45.9	151.9 ± 72.6	0.000*
HbA1c, %	6.3 ± 1.4	7.0 ± 1.8	6.1 ± 1.0	6.1 ± 1.1	6.0 ± 1.1	0.000*
Creatinine, mg/dl	1.2 ± 1.0	1.1 ± 0.5	1.1 ± 0.9	1.2 ± 1.0	1.4 ± 1.5	0.000*
WBC, 10^9/L	8.5 ± 4.8	8.4 ± 3.1	8.5 ± 6.4	8.5 ± 4.2	8.9 ± 4.8	0.159
Postoperative laboratory indicators						
Glucose max, mg/dl	170.0 ± 59.1	142.3 ± 38.0	146.1 ± 32.5	164.7 ± 41.8	217.6 ± 80.2	0.000*
Creatinine, mg/dl	1.2 ± 1.0	1.0 ± 0.6	1.1 ± 0.9	1.2 ± 0.8	1.5 ± 1.5	0.004*
WBC, 10^9/L	17.2 ± 8.7	16.5 ± 6.1	17.2 ± 11.8	17.3 ± 6.6	17.7 ± 9.0	0.000*
Vital signs						
HR Mean, beats/min	80 ± 12	80 ± 11	79 ± 11	80 ± 11	83 ± 14	0.000*
RR Mean, times/min	16 ± 4	15 ± 4	16 ± 4	16 ± 4	17 ± 5	0.000*
SBP Mean, mmHg	114 ± 18	114 ± 18	114 ± 18	113 ± 18	115 ± 19	0.320
DBP Mean, mmHg	60 ± 12	60 ± 11	59 ± 11	59 ± 11	60 ± 13	0.126
Temperature Mean, ℃	36.2 ± 0.7	36.3 ± 0.6	36.2 ± 0.7	36.3 ± 0.7	36.3 ± 0.7	0.064
Aps iii	34 (26, 45)	32 (25, 41)	32 (25, 42)	33 (26, 44)	38 (29, 51)	0.000*
Mechanical ventilation time, (h)	28 (19, 56)	25 (19, 46)	26 (19, 47)	29 (18, 55)	40 (20, 73)	0.000*
LOS in ICU, (d)	2 (1, 3)	1 (1, 3)	2 (1, 3)	2 (1, 3)	2 (1, 4)	0.000*
LOS in hospital, (d)	8 (7, 11)	9 (7, 11)	8 (6, 11)	8 (6, 12)	10 (7, 14)	0.000*
Clinical outcomes						
In-hospital mortality, (%)	83 (2.2)	9 (0.9)	7 (0.7)	19 (2.0)	48 (4.9)	0.000*
30-day mortality, (%)	76 (2.0)	10 (1.0)	8 (0.9)	12 (1.2)	46 (4.7)	0.000*
90-day mortality, (%)	150 (3.9)	27 (2.8)	15 (1.6)	31 (3.2)	77 (7.9)	0.000*
360-day mortality, (%)	279 (7.3)	55 (5.7)	42 (4.5)	60 (6.2)	122 (12.5)	0.000*

*Statistically significant: a value greater than 0.05 is interpreted as a meaningful difference

SHR, Stress hyperglycemia ratio; BMI, Body mass index; MI, Myocardial infarction; HF, Heart failure; CVD, Cerebrovascular disease; AF, Atrial fibrillation; ICU, Intensive care unit; WBC, White blood cells; HbA1c, Hemoglobin A1c; HR, Heart rate; SBP, Systolic blood pressure; DBP, Diastolic blood pressure; RR, Respiratory rate; LOS, Length of Stay; Aps iii, Acute Physiology Score III; ICU, Intensive care unit;

Table 2 Logistic regression models for hospital, 30-day, 90-day and 360-day all-cause mortality

Variables	In-hospital mortality	*P* value	30-day mortality	*P* value	90-day mortality	*P* value	360-day mortality	*P* value
	HR (95%CI)		HR (95%CI)		HR (95%CI)		HR (95%CI)	
Postoperative SHR quantile								
Q1	1.00 (Reference)		1.00 (Reference)		1.00 (Reference)		1.00 (Reference)	
Q2	0.730 (0.241, 2.205)	0.576	0.707 (0.262, 1.913)	0.495	0.545 (0.275, 1.079)	0.082	0.699 (0.448, 1.902)	0.116
Q3	1.805 (0.764, 4.267)	0.178	0.994 (0.409, 2.420)	0.990	1.015 (0.580, 1.777)	0.959	0.939 (0.624, 1.412)	0.763
Q4	3.323 (1.558, 7.089)	0.002*	2.877 (1.391, 5.590)	0.004*	1.918 (1.187, 3.099)	0.008*	1.485 (1.031, 2.138)	0.034*
HR for trend	1.651 (1.304, 2.091)		1.623 (1.275, 2.066)		1.371 (1.165, 1.613)		1.208 (1.073, 1.359)	
P for trend		0.000*		0.000*		0.000*		0.002*

*Statistically significant: a value greater than 0.05 is interpreted as a meaningful difference

SHR, Stress hyperglycemia ratio; HR, Hazard ratio; CI, Confidence interval;

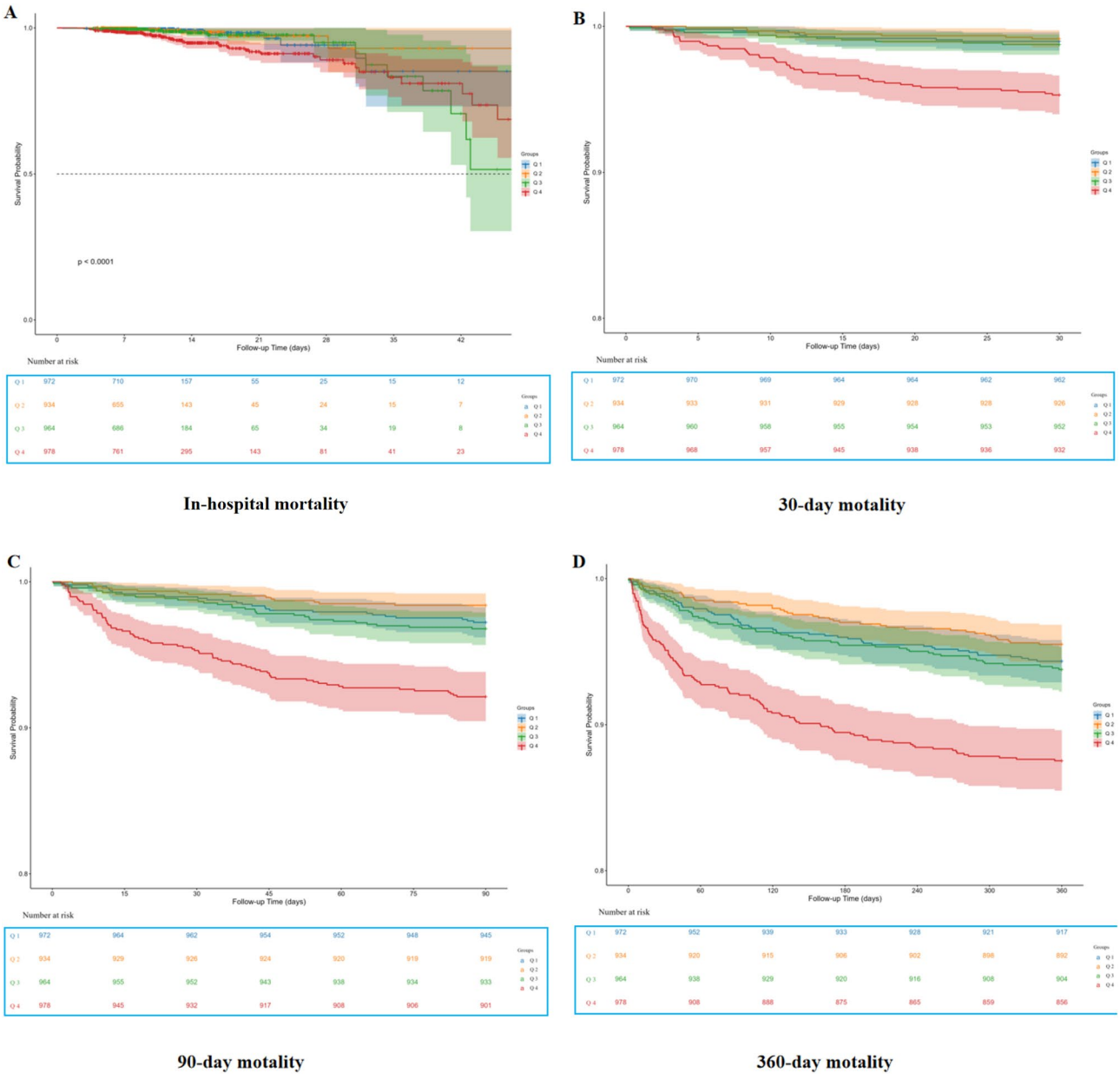

Fig. 2 Kaplan–Meier survival analysis curves for all-cause mortality. Kaplan–Meier curves of hospital (**A**) 30-day (**B**), 90-day (**C**) and 360-day (**B**) all-cause mortality stratified by postoperative *SHR* index, *SHR* Stress hyperglycemia ratio

postoperative SHR was no associated with 30-day mortality among females, individuals aged < 75 years, those with creatinine levels ≤ 90, and patients without MI, heart failure, CVD, pulmonary disease, or renal disease. However, postoperative SHR was significantly associated with 360-day mortality among those without HF.

Mediation analysis

Mediation analysis, conducted on 2,649 patients with complete data for monocytes, neutrophils, lymphocytes, and platelets, demonstrated that postoperative SHR indirectly influenced prolonged mechanical ventilation through its association with inflammatory markers (eTable 1). These markers include the neutrophil-to-lymphocyte ratio (NLR), monocyte-to-lymphocyte ratio (MLR), platelet-to-lymphocyte ratio (PLR), systemic immune-inflammation index (SII), and systemic inflammation response index (SIRI). Prolonged mechanical ventilation, in turn, was associated with increased 30-day mortality risk ($p < 0.05$) (eTable 2, eFigure 3).

Machine learning

Using six machine learning algorithms were used to predict in-hospital all-cause mortality and were further

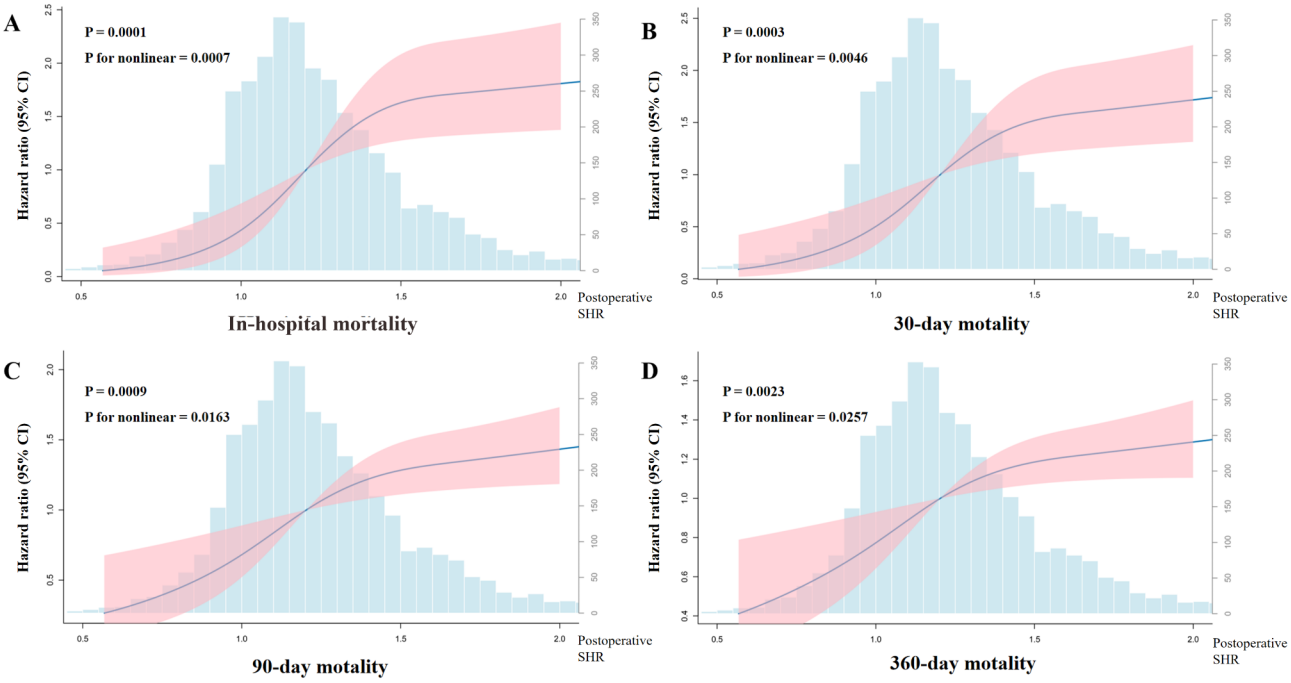

Fig. 3 RCS of SHR index with all-cause mortality. RCS of postoperative SHR index with hospital A 30-day **B**, 90-day **C** and 360-day **B** all-cause mortality. *SHR* Stress hyperglycemia ratio, *RCS* Restricted cubic splines

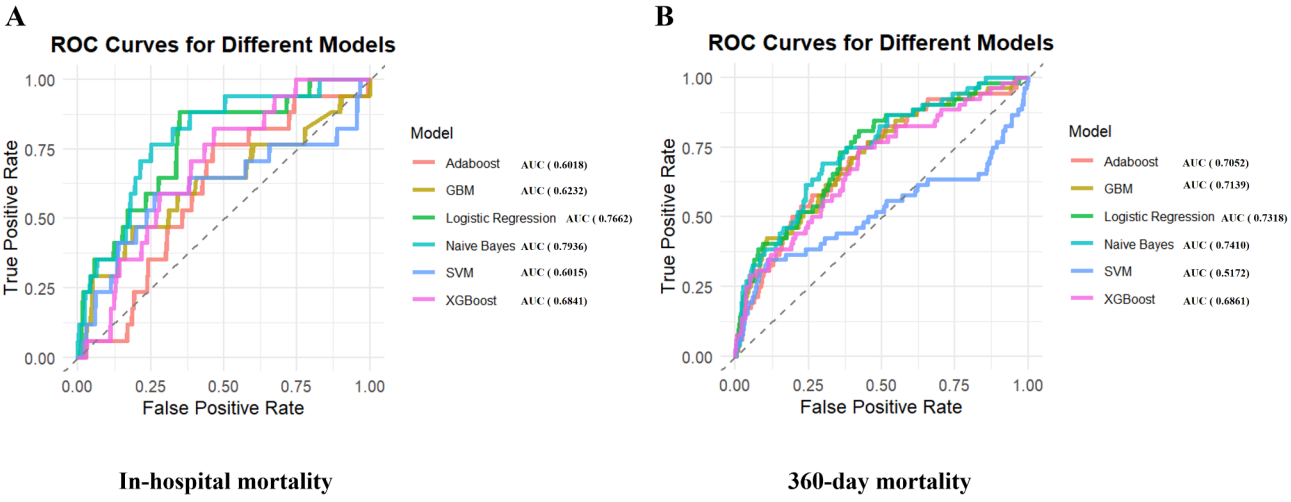

Fig. 4 The machine learning algorithm predicts in-hospital and 360-day all-cause mortality. *AUC* Area under the curve, *XGBoost* Extreme gradient boosting, *SVM* Support vector machine, *AdaBoost* Adaptive boosting, *GBM* Gradient boosting machine

extended to predict 360-day all-cause mortality. The model incorporated creatinine, SHR, HR, RR, HF. NB algorithm demonstrated the strongest predictive performance on in-hospital and 360-day all-cause mortality, achieving an AUC of 0.7936 and 0.7410 comparing with other models. (Fig. 4, eFigs. 7 and 8).

Discussion

This study, to our knowledge, is the first investigation examining the association between postoperative SHR levels and in-hospital, 30-day, 90-day and 360-day all-cause mortality in patients undergoing cardiac surgery. Our results reveal a non-linear relationship between SHR levels and in-hospital mortality, as well as mortality at 30, 90, and 360 days following surgery. Notably, elevated postoperative SHR levels are associated with an increased risk of in-hospital, 30-day, 90-day and 360-day all-cause mortality, potentially mediated through mechanisms such as inflammation and prolonged mechanical ventilation. These findings provide critical insights that may inform strategies aimed at mitigating mortality risk in patients undergoing cardiac surgery.

The stress-induced hyperglycemia is commonly observed in patients following surgery, which is close association with all-cause mortality [15]. Postoperative hyperglycemia primarily arises as a consequence of the body's stress response to surgical intervention, involving factors such as trauma, anesthesia, pain, and inflammation [21]. These stressors activate elevated levels of stress hormones, including cortisol, catecholamines, and glucagon, which promote hepatic glucose production and inhibit peripheral glucose uptake [22]. A body of research has established hyperglycemia as a significant risk factor for postoperative complications, which are closely associated with increased in-hospital mortality [13]. However, traditional measurements of blood glucose, both pre- and post-admission, fail to capture the dynamic fluctuations in blood glucose levels. In this context, SHR provides a more robust and reliable metric for evaluating stress-induced hyperglycemia [11]. Existing literature consistently underscores the clinical relevance of SHR, linking it to critical factors such as thrombus load, the severity of coronary artery disease, post-stroke cerebral edema, and an increased risk of infection during hospitalization [23, 24, 25]. Furthermore, SHR has demonstrated predictive utility for clinical outcomes, with elevated SHR levels being significantly associated with long-term 1-year all-cause mortality in cohorts from both the United States and China [26]. Additionally, in patients with acute decompensated heart failure, SHR exhibits a U-shaped relationship with long-term mortality and readmission rates [9]. SHR has also been shown to be independently associated with the risk of major adverse cardiovascular events (MACE) [27]. In our study, elevated postoperative SHR levels are strongly associated with an increased risk of in-hospital, 30-day, 90-day and 360-day all-cause mortality, following a non-linear pattern when compared to preoperative SHR levels.

Another key finding of our study is that inflammation acts as a mediating factor between postoperative SHR and 30-day, 90-day and 360-day all-cause mortality risk. Hyperglycemia exacerbates mortality by disrupting glucose metabolism and triggering systemic inflammation. Elevated blood glucose significantly increases the expression of inflammatory markers, which, in turn, contribute to the development of insulin resistance and impairment of blood glucose control, creating a vicious cycle. The inflammatory response also leads to multi-organ dysfunction, particularly affecting the heart, kidneys, and liver [28]. These markers impair endothelial cell function, induce oxidative stress, and activate immune cells, all of which contribute to organ failure [29]. Additionally, hyperglycemia increases the risk of postoperative infection, prolonged hospital stays, and elevates the incidence of complications, ultimately adversely affecting patient prognosis and quality of life [26, 30]. Our study underscores the role of hyperglycemia in amplifying mortality risk through heightened inflammation, including NLR, MLR, PLR, SII, and SIRI, which contribute to prolonged mechanical ventilation. It is crucial to emphasize that this association is indirect. Inflammation is identified as a prognostic factor for an extended duration of mechanical ventilation, and subsequently, this prolonged mechanical ventilation is associated with an elevated risk of mortality within a 30-day timeframe, but not for all time intervals of mortality. Moreover, hyperglycemic conditions may create an environment conducive to bacterial and other pathogenic infections, further prolonging mechanical ventilation durations and exacerbating postoperative mortality rates.

Beyond its influence on short-term outcomes, stress-induced hyperglycemia also plays a significant role in long-term mortality risks. While the association between postoperative SHR and increased short-term mortality following cardiac surgery is well-documented, emerging evidence suggests that it is also linked to long-term mortality. For instance, elevated SHR levels are significantly associated with long-term all-cause mortality in cohorts from both the U.S. and China [26]. In our study, postoperative SHR is significantly correlated with both 30-day and 360-day mortality risks and is a good marker for the prediction of 30-day all-cause mortality. However, the predictive accuracy for 360-day mortality is relatively modest, and additional clinical variables are required to enhance the prediction of long-term mortality. To address this limitation, we developed a predictive model that integrated both preoperative variables. We used six machine learning algorithms [31] to predict in-hospital all-cause mortality and subsequently extended them to forecast 360-day all-cause mortality, which demonstrates strong predictive performance. The model incorporated patient demographics, preoperative health status, postoperative recovery metrics, and relevant physiological markers, offering a more precise and personalized risk assessment. In comparison to traditional risk models, this machine learning-based approach accounted for intricate interactions between variables and can dynamically adjust based on individual patient characteristics. Consequently, it provides clinicians with a more refined tool for early identification of high-risk patients, thereby facilitating timely interventions that may improve long-term survival outcomes.

Our findings further suggest that SHR, when combined with HbA1c levels and initial blood glucose at admission, can serve as an effective and practical alternative for evaluating cardiac surgery patients. As a simple and readily available tool, the SHR index can assist clinicians in quickly identifying high-risk patients, potentially reducing mortality rates and improving overall patient outcomes. However, several limitations must be

considered in interpreting our findings. First, the retrospective nature of our study, along with the use of data from a single medical center and reliance on the MIMIC-IV database, limits our ability to establish causal relationships. Although we adjusted for various confounders and performed subgroup analyses, residual confounding factors might still influence the results. Additionally, the moderate sample size calls for validation of these findings in larger cohort studies. Lastly, while our study provides strong associations between SHR and 30-day, 90-day and 360-day all-cause mortality, we are unable to fully elucidate the biological mechanisms underlying this relationship, which may limit the broader applicability of our conclusions.

Conclusion

In our study, postoperative SHR appeared to be an effective, non-invasive measure for predicting short-term and long-term mortality outcomes in cardiac surgery patients. This study highlights the potential of SHR as a tool for identifying high-risk patients and improving clinical decision-making. Further prospective studies with larger sample sizes are needed to confirm these findings and explore the clinical utility of SHR in enhancing postoperative care and outcomes.

Abbreviations

SHR	Stress hyperglycemia ratio
BMI	Body mass index
MI	Myocardial infarction
HF	Heart failure
CVD	Cerebrovascular disease
AF	Atrial fibrillation
ICU	Intensive care unit
WBC	White blood cells
HbA1c	Hemoglobin A1c
HR	Heart rate
SBP	Systolic blood pressure
DBP	Diastolic blood pressure
RR	Respiratory rate
T	Temperature
LOS	Length of stay
HR	Hazard ratio
CI	Confidence interval
MIMIC-IV	Medical information mart for intensive care IV
Aps iii	Acute Physiology Score III
NLR	Neutrophil-to-lymphocyte ratio
MLR	Monocyte-to-lymphocyte ratio
PLR	Platelet-to-lymphocyte ratio
SII	Systemic immune-inflammation index
SIRI	Systemic inflammation response index
RCS	Restricted cubic splines
AUC	Area under the curve
IQR	Interquartile ranges
KM	Kaplan–Meier
XGBoost	Extreme gradient boosting
SVM	Support vector machine
AdaBoost	Adaptive boosting
NB	Naive bayes
LR	Logistic regression
GBM	Gradient boosting machine

Supplementary Information

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Supplementary Material 1.

Supplementary Material 2.

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Data sharing

To obtain this data-sets, interested parties should submit a formal request. This request should be addressed to the corresponding author of this study.

Author contributions

YP and YM performed the analysis and drafted the manuscript. JL and YZ provided clinical advice and managed the significance of clinical metrics. YP and YF assisted in creating and revising the tables and figures. WL, YF, and GZ performed the secondary checking of data and of tables and graphs. YX, JL and YZplanned and supervised the study and were involved in revising the manuscript. All authors gave final approval of the version to be published.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Competing interests

The authors declare no competing interests.

Ethics approval and consent to participate

The data was extracted from Medical Information Mart for Intensive Care IV (MIMIC-IV, Version 2.2). The identification information was concealed and privacy of patients in MIMIC-IV were protected. Thus, there were no additional consent procedures from institutional ethics committee.

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